# Classification Of Wheat Crop Using Remotely Sensed Multi-Spectralplanet-Scope Temporal Data

**Awab Ur Rashid Durrani, Arbab Masood Ahmad**

**Abstract:** Agriculture plays a vital role in the economies of developing countries and provide the mainsource of food, income and employment for general public. Monitoring and assessment of the crop yieldis a crucial task and is critical in ensuring good agricultural management. We propose the monitoring andclassification of wheat crops through remote sensing by utilizing satellite imagery. In our research work,we have utilized multi-spectral imagery of Planet-Scope satellite for the classification of wheat crop. Theimagery used is a temporal stack of remotely sensed imageries obtained on various dates with reference tothe phenological cycle of wheat.We employ three different machine learning classifiers i.e., Artificial NeuralNetwork (ANN), Support Vector Machine (SVM) and Minimum Distance (MD) classifier for the wheatcrop classification. Confusion matrix and Kappa Coefficient(Kappa Coefficient) analyzes the performanceof these three classifiers. The results obtained shows that ANN with an overall accuracy of 98:7031%and Kappa Coefficient equivalent to 0:9825 outperforms the SVM and MD classifiers having the overallaccuracy of 85:2005% and 73:1604% and Kappa Coefficient values of 0:8097 and 0:6455, respectively.

**Index Terms**: Remote sensing, Classification, Temporal, Artificial neural network, Support vectormachine, Minimum distance, Planetscope.

## 1 INTRODUCTION

Wheat and associated products are a major source of nutritionin South Asian countries including Pakistan, India,Afghanistan and Bangladesh [1]. Pakistan is a developingcountry with limited resources for regular monitoring andestimation of wheat crop on a diverse landscape [2]. Thelack of proper management of wheat crop and yield statisticsresults in various issues such as overstocking by stakeholders,over pricing and illegal sales and exports. The existingwheat crops estimation in Pakistan relies on farmers feedbackabout the harvested crop data, which is greatly susceptible tohuman manipulation and is therefore not very reliable [3].Precision agriculture's goal is to increase the intelligencein the production of the agricultural crop, using real-timesensing, control and optimization for enhancing soil-crophealth as well as advanced cyber-enabled tools for automatedand efficient agricultural crop detection and estimation.The last few decades have witnessed enormous scientificand technological advancement in the field of precision agriculture.One of the marvels of technological advancements isthe use of remotely sensed satellite data for monitoring theagricultural crops. Remote sensing has been the center of research and developmentin the last few decades. The advancement inremote sensing has resulted in an improved satellite imagingsystems and highly precised agriculture research [4]. Thedata obtained through the satellite imagery is vital for usagein agricultural research, geological research and strategicland-use analysis and planning. Remote sensing techniquesare used to detect and estimate different types of vegetation [5]. The emerging trends in the field of precision agriculture, advancement in intelligent crop monitoring systems, availabilityof efficient remote sensing capabilities and accessibilityto advanced cyber-physical tools can greatly benefit theagricultural crop monitoring and production. In the past the research has paid less attention to the use ofremote sensing technology for crop monitoring, analysis andestimation. This is mainly because of the huge cost incurreddue to high resolution satellite imageries, the non availabilityof accurate data and trained human resources. Lately, thelaunch of high resolution commercial as well open sourcesatellites have throttled the remote sensing research [6], [7]. Satellite imageries are associated with three main featuresnamely spatial, spectral and temporal resolutions. Spatialresolution captures per pixel covered area of the land, whilethe spectral resolution is related to the employed spectralwavelengths from the imaging source. However, temporalresolution pertains to the rotational distance between anytwo images apart in time but belonging to identical location. The effective utilization of these features help us in theidentification and estimation of various types of crops. This manuscript proposes a machine learning based techniquefor the detection and estimation of wheat crops in thesub-region of Khyber Pakhtunkhwa province of Pakistan. We performed our testing in agricultural research farm ofUniversity of Peshawar (UOP) as a pilot region. We utilizedtemporal based features of wheat crop detection andestimation. The supervised classifiers used for detection andestimation are Artificial Neural Network (ANN), SupportVector Machines (SVM) and Minimum Distance (MD). The rest of the manuscript is the organized as follows. Section II discusses the related work. Section III illustratesthe study area. Section IV encompasses the data description. The methodology is captured in section V. Section IV demonstratesthe results, while Section V concludes the paper.

## 2 RELATED WORK

Crop yield estimation in Pakistan is mainly based on theconducted manual land surveys. The area covered by a cropis estimated by the land record officer known as Patwari, who maintains the land record document known as Girdwariin Pakistan. The data from these surveys are collected bythe Agriculture, Irrigation and Planning and Developmentdepartments for establishment of policy and decision makingpurpose. Whereas the final yield estimation is done by the useof sampling techniques, which are approved by provincialagriculture statistics coordination board [8]. The productivityof a crop is dependent on various factors such as soil type, seed variety, fertilizer type and proper timings for sowing theseeds. Therefore, quality and quantity of yield expected fromthe crop depends on the conditions faced by the crop. HaoweiMu et al make use of multi-temporal MODIS images inorder to estimate the crop yield for winter wheat. Histogramdimensionality reduction and time series fusion is

used as aninput layer for Convolutional Neural Networks(CNN). CNNnetwork was used to extract the features of winter wheatgrowth [9]. Omer Vanli et al. compared different classificationtechniques such as Maximum Likelihood, SupportVector Machine, Condition-based and Nearest Neighbourusing Landsat 8 data to estimate wheat crop production.Theperformance analysis were performed, which showed that theSupport Vector Machine classifier performed better than allother employed classifiers [10]. Feng Xu et al. combinedLandsat 8 and Sentinel-2 temporal images and performedclassification with Random forest classifier, obtaining 93.4%of overall accuracy and compared the obtained results withthe classification performance of mono-temporal imagery, which resulted in 76.4% of overall accuracy [11]. Researchon the relationship between wheat protein content and wheatagronomic parameters at different growing stages withLandsatTM multi-temporal images has been done by LI Cun-junet al. using partial least squares [12]. Peng YANG et al. estimatedwheat yield using multi-temporal Landsat ™ imagesand GIS based model to improve the yield estimation accuracyof crop growth model [13]. Multiple images of Landsat 5acquired at different growth stages of wheat crop and its LeafArea Index (LAI) were calculated for all three stages, i.e.jointing, flowering and milking, for estimating crop growthby S Xiaoyu et al. [14]. Jinran Liu et al used spectral indicesfor wheat coverage prediction by using multispectral images,collected through Unmanned Aerial Vehicle (UAV) equippedwith RedEdge-M sensors [15]. Mengmeng Du et al listedapplications of remote sensing using UAV in agriculture, thathave proved to be an effective and efficient way of obtainingfield information. Furthermore, the feasibility of utilizingmulti-temporal color images acquired from a low altitudeUAV-camera system to monitor real-time wheat growth statusand to map within-field spatial variations of wheat yield forsmallholder wheat growers, was investigated [16].Wen Zhuoet al. Estimated crop production at a geographical scale overa long period by the soil via images retrieved by a water cloudmodel that uses SAR and optical data [17]. Liu Liangyun etal. acquired Landsat ™ images at different stages of wheatcrop for its growth monitoring and yield estimation. Firstly,satellite imagery is utilized at seed time along with its NDVIand then in the second stage the yield estimation modelwas implemented and tested using three imageries of allthree stages i.e. Heading, grain filling and milking of wheatcrop [18]. There is an emerging trend in the development ofremote sensing based cyber physical system for monitoringof earth resources. In [19], a smart cyber physical systemis developed for wastewater management. Remote sensingtechnologies were utilized to gather large quantity of waterquality information and to efficiently process it through cyberinterfaces for provision of early information for wastewatertreatment and decision making. Similarly, in [20], a spacebasedcyber-physical system is proposed in order to addressthe rising demand for development of low cost and timeefficient satellite system for earth resources monitoring. Furthermore, an adaptive Sensor-Drone-Satellite (SeDS) systemfor precision agriculture to overcome the challenges of lowercost and time efficiency is proposed in [21].

**TABLE** 1

BAND COMPOSITION OF PLANETSCOPE'S DOVE

| Bands | Names | Wave length (μm) | Resolution (m) |
|---|---|---|---|
| Band-1 | Blue | 0.49 m | 3-5m |
| Band-2 | Green | 0.55 m | 3-5m |
| Band-3 | Red | 0.63 m | 3-5m |
| Band-4 | Near Infra-Red (NIR) | 0.82 m | 3-5m |

## 3 STUDY AREA

In our experimental setup, we considered the research farm of Agriculture University, Peshawar, Pakistan as a pilot region. The selected pilot region which is shown in Fig. 1 consistsof various agricultural crops, including wheat, Clover, Mustard and Urban.

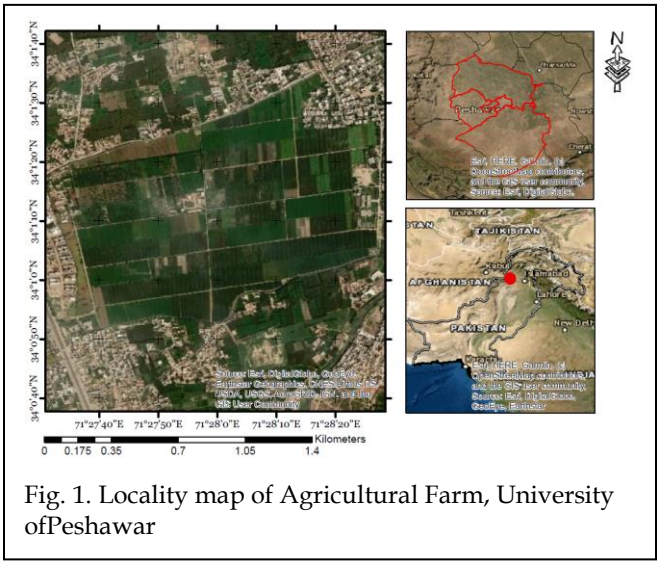


Fig. 1. Locality map of Agricultural Farm, University ofPeshawar

## 4 DATA DESCRIPTION

Data used in our research is acquired from Planet Inc. PlanetInc is a private earth imaging company based in California, America. In 2015, the International Space Station (ISS) launched the first dove nano satellite from on behalf of PlanetInc. Dove has spatial resolution of 2.7m to 3.2m in ISS orbit, while 3.7m -to- 4.9m in sun synchronous orbit as presentedin Table 1. Dove provides global coverage of 4 channels, including Red, Green, Blue and Near Infrared Reflectance (NIR) to the Geo analysts with a temporal resolution of oneday. This makes Dove an attractive option for the observationof Geo events, change detection and monitoring. In thisstudy, the acquired image scenes were atmospherically andradiometrically corrected and the regions of interest used asground truth data were recorded from all the retrieved scenes.

## 5 METHODOLOGY

Figure 3 represents the process diagram of our adoptedmethodology. Eight (8) scenes of PlanetScope surface reflectanceimages were retrieved comprising of 08th and 15th of February, 2nd, 15th and 29th of March and 2nd, 21st and 30th of April, 2020. These specific dates for retrievalof PlanetScope imagery were selected while keeping in viewthe phenological cycle of wheat in Pakistan and favourableclimatic conditions. Figure 4 represents time variant spectralcharacteristics for the selected 8 categories of crops in nearinfrared (NIR) band. It can be observed from the spectral reflectancecurves that wheat crop has highest NIR reflectanceprofile on 2nd of March. This trend keeps gradually decliningtill 30th April, when the wheat crop reaches its final stage ofgrowth cycle. A survey for collection of the ground truth datawas conducted in the designated pilot region. We

used ournative android based Geo survey application i.e., GeoSurvey [22] for conducting the survey. The ground truth data is splitinto 60% training and 40% test data. The 60% training data isfed to the classifiers for training purpose. In order to validateand evaluate the performance of the considered classifiers, the 40% test set data is used.

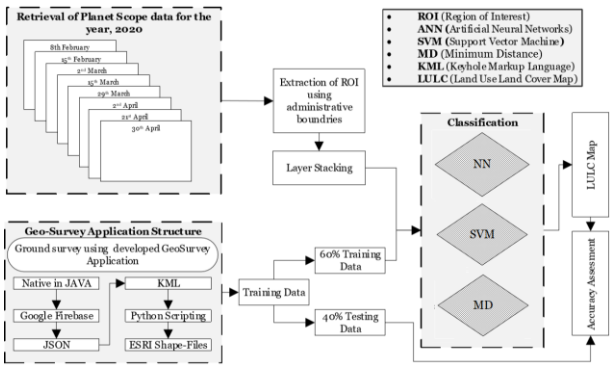


Fig. 3. Process Diagram of the proposed Methodology

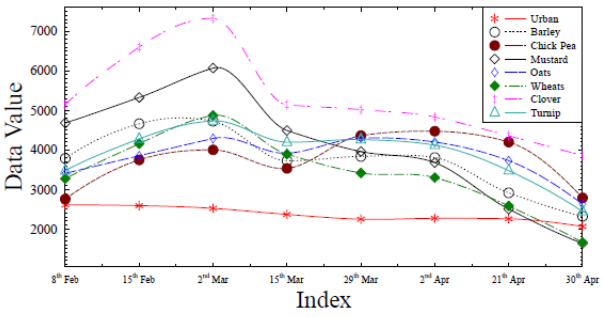


Fig. 4. Spectral profile of crop categories in the area of observation

### 5.1 Survey For Ground Truth Data

A survey to collect the training data was conducted in the designated pilot region using GeoSurvey application. The interface details of the application is provided in Figure 2.


Fig. 2. (a) GEOSurvey selection modes. (b) Drawing apolygon by tapping on google map. (c) Viewing the surveydata on map. (d) View data as a list.

Our survey classes include:
1) wheat
2) Urban
3) Turnip
4) Clover
5) Oats
6) Mustard
7) Chick Pea
8) Barley

The data collected during the survey is saved in Googleapplication development software - firebase. Then it is downloadedin JavaScript Object Notation (JSON) lightweightformat, which is converted into Keyhole Mapping Language (KML) file format through python scripting. Such file formatcan be used to display geographic data in an Earth browsersuch as Google Earth. ArcGIS is used to convert KMLfiles to shape files into a geospatial vector data format thatcan be used as training data. The GeoSurvey applicationfor survey has an additional advantage of cost and timeeffectiveness.TheGeoSurvey application can be utilized toperform survey using any of the following two modes:

- Walking survey mode: It can be used by the surveyorsfor collecting several points from the underlying landcoverby walking around the region of interest. Polygonwill be drawn on the map once the survey of the field iscompleted by the surveyor.
- Manual survey mode: It can be used by the surveyors forcollecting several points by tapping on the map. Polygonwill be drawn on the map once the surveyor completethe points selection on the map for the region of interest.
- Similarly, surveyed data can be viewed using twomodes.
- View data as polygon shows polygons of different categorieson the google map. Furthermore, view data as alist that captures the list of all polygons
- Each polygon can be associated with a specific categoryi.e., wheat, Urban, Clover etc.

### 5.2 Training

The training data collected through ground truth surveys isclassified into eight different classes. These classes includewheat, Urban, Turnip, Clover, Oats, Mustard, Chick Peaand Barley. The data is divided into 60% training and 40%testing. The training data is fed to classifiers for their training.The performance of the target classifiers is validated against40% testing data.

### 5.3 Accuracy Assessment

To measure the performance of the proposed mechanism,various accuracy metrics such as overall accuracy, user accuracy,producer accuracy and confusion matrix are considered.These accuracy metrics are explained below.

#### 5.3.1 Overall Accuracy (OA)

Overall accuracy is measured by the ratio of exactly classifiedpixels to the total number of pixels. Mathematically, anoverall accuracy is written as:

$$OA = \frac{No.of Exactly classified Pixels}{Total No.of Pixels} \qquad (1)$$

#### 5.3.2User Accuracy (UA)

The relationship of the exactly classified pixels for a specific class to the total number pixels classified into that class. It is

related to the error of commission.

$$UA = \frac{Exactlyclassifiedpixelsforaparticularclass}{Total\#ofPixelsclassifiedintothatclass} \quad (2)$$

**5.3.3Producer Accuracy (PA)**
Producer accuracy is the relationship between exactly classifiedpixels for a class to the total number of pixels for that class. It is related to the error of omission.

$$PA = \frac{ExactlyClassifiedpixelsforaclassTotalNo.ofPixelsforthatclass}{} \quad (3)$$

**5.3.4Error of Omission (OE)**
Error of omission shows the selection of values that belongsto a class but were predicted to be in a different class. Theyare a measure of false negatives. Errors of omission areshown within columns of the confusion matrix apart from thevalues along the diagonal. This type of error is additionally
referred to as type I error.

$$OE = \frac{ExactlyClassifiedpixelsforaclassTotalNo.ofGroundtruthsamples}{} \quad (4)$$

**5.3.5Error of Omission (OE)**
Errors of commission show the selection of values that were predicted to be in a very class but do not belong to that class. They are a measure of false positives. Errors of commissionare shown within rows of the confusion matrix apart from thevalues along the diagonal. This type of error is referred to as

TABLE 2
ANN PARAMETERS

| Parameters | Values |
|---|---|
| Training Threshold Contribution | 0.9 |
| Training Rate | 0.1 |
| Training Momentum | 0.9 |
| Training Root Mean Square(RMS) Exit Criteria | 0.1 |
| Number of Hidden Layers | 1 |
| Number of Training Iterations | 500 |
| Min Output Activation Threshold | 0.07 |

type II error.

$$CE = \frac{Incorrectlyclassifiedsites}{TotalNo.ofclassifiedsites} \quad (5)$$

5.4 Supervised Classification Algorithms
In our experimental setup the following classifiers wereemployed in order to investigate their classification performance.

**5.4.1Artificial Neural Networks**
input layer, an output layer, and a hidden layer was used. A multi-layered feed-forward ANN is used to perform nonlinear classification and uses back propagation for supervisedlearning.This model has been designed through its motivation fromthe brain neural system, thus using neural networks in theprocess. Performance of an ANN classifier can be improvedby adjusting weights of the interconnected nodes. The networkgives feedback after processing the input data and ifthere is an error, it is corrected by adjusting the networkweights using recursive method [23]. The input values aresummed up and passed through activation function. TheANN with temporal features is illustrated visually in Figure5.

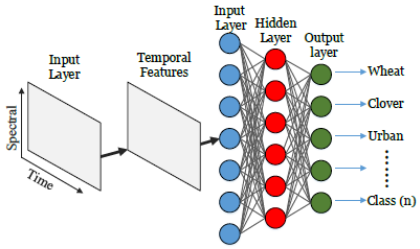


Fig. 5. Representation of Artificial Neural Networkswith Temporal Features

Different parameters that control the performance of Neural network are defined as follows;

- Training Threshold Contribution: It helps in determininghow much internal weight has contributed withrespect to the activation level of the node.
- Training Rate: It works in identifying the magnitude ofthe weight adjustment for the specific nodes.
- Training Momentum: It helps in preventing the systemfrom converging to a local minimum.
- Training Root Mean Square(RMS) Exit Criteria: RMSerror is introduced to stop the algorithm from furthertraining.
- Number of Hidden Layers: It adds additional mathematicalcalculations.
- Number of Training Iterations: It determines the numberof iterations for which training of the algorithm shouldcontinue.
- Min Output Activation Threshold: It determines thethreshold value for a pixel, below which the pixel islabeled as unclassified.

The values used for various parameters of ANN are shown in Table 2

**5.4.2Support Vector Machine Classifier (SVM)**
SVM is a supervised, non-parametric classification algorithm derived from statistical learning theory [24]. It separates theconsidered classes with a decision surface that maximises thedistance between the classes. The decision surface is calleda hyper-plane and the decision points that are nearer to hyper-planes are called support vectors which is pictoriallypresented in Figure 6.

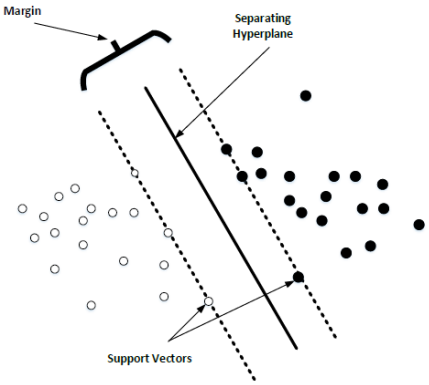


Fig. 6. Representation of Hyper-Plane in Kernel Function

SVM can perform nonlinear classificationby using various types of kernels, which converts thenonlinear boundaries to linear one [25]. The SVM classifieris mathematically defined as;

$$w.x + b = 0 \qquad (6)$$

Where b and w are the parameter of the hyper-plane.Vectorswhich are not in hyper plane are presented by;

$$w.x + b > 0 \qquad (7)$$

Whereas the two margins are presented by;

$$w.x + b = -1 \qquad (8)$$

And

$$w.x + b = +1 \qquad (9)$$

Kernel type: SVM uses various mathematical functions called kernels. Kernel functions take data as input andtransform it into the required form. These functionsare Linear, Non linear, polynomial, radial basis function(RBF) and sigmoid.

- Gamma in kernel Function: Gamma parameter is theinverse of the standard deviation of the RBF kernel.The gamma parameter defines the effect of a singletraining example, with low values making a loose fit ofthe training data, while high values make it fit accuratelyfor the model.
- Penalty parameter: The penalty parameter 'C' controlsthe tradeoff between allowing training error and forcingrigid margins. When the value of C is large, theoptimization will be a smaller margin hyperplane thentraining data will be classified correctly.
- Pyramid Level and Classification Probability Threshold:Pyramid level sets the number of hierarchical processinglevels to apply during the svm training and classification.Where classification probability threshold setsthe probability that is required for the svm classifier toclassify a pixel. Table 3 present the parameters values ofSVM.

TABLE 4
CLASSIFICATION RESULTS OF ARTIFICIAL NEURAL NETWORKS

| Classes | Commission Error % | Omission Error % | Producer Accuracy % | User Accuracy % |
|---|---|---|---|---|
| Wheat | 1.05 | 0.47 | 99.53 | 98.95 |
| Urban | 0.00 | 0.00 | 100.00 | 100.00 |
| Turnip | 0.67 | 0.60 | 99.40 | 99.33 |
| Clover | 0.05 | 0.04 | 99.96 | 99.95 |
| Oats | 0.22 | 0.78 | 99.22 | 99.78 |
| Mustard | 0.21 | 0.34 | 99.66 | 99.79 |
| Chick Pea | 14.71 | 0.00 | 100.00 | 85.29 |
| Barley | 0.53 | 31.95 | 68.05 | 99.47 |
| OA | 98.7031% | | | |
| Kappa Coefficient | 0.9825 | | | |

TABLE 5
CLASSIFICATION RESULTS OF SUPPORT VECTOR MACHINES

| Classes | Commission Error % | Omission Error % | Producer Accuracy % | User Accuracy % |
|---|---|---|---|---|
| Wheat | 0.44 | 9.70 | 90.30 | 99.56 |
| Urban | 0.00 | 11.93 | 88.07 | 100.00 |
| Turnip | 0.71 | 42.66 | 57.34 | 99.29 |
| Clover | 0.05 | 3.04 | 96.96 | 99.95 |
| Oats | 0.52 | 26.99 | 73.01 | 99.48 |
| Mustard | 0.15 | 10.44 | 89.56 | 99.85 |
| Chick Pea | 0.00 | 36.62 | 63.38 | 100.00 |
| Barley | 0.00 | 54.45 | 45.55 | 100.00 |
| OA | 85.2005% | | | |
| Kappa Coefficient | 0.8097 | | | |

***TABLE 6***
***CLASSIFICATION RESULTS OF MINIMUM DISTANCE***

| Classes | Commission Error % | Omission Error % | Producer Accuracy % | User Accuracy % |
|---|---|---|---|---|
| **Wheat** | 10.99 | 30.42 | 69.58 | 89.01 |
| **Urban** | 0.00 | 0.00 | 100.00 | 100.00 |
| **Turnip** | 82.87 | 85.58 | 14.42 | 17.13 |
| **Clover** | 4.28 | 3.65 | 96.35 | 95.72 |
| **Oats** | 17.53 | 55.67 | 44.33 | 82.47 |
| **Mustard** | 50.29 | 18.54 | 81.46 | 49.71 |
| **Chick Pea** | 92.88 | 8.62 | 91.38 | 7.12 |
| **Barley** | 68.47 | 68.41 | 31.59 | 31.53 |
| **OA** | 73.1604% | | | |
| **Kappa Coefficient** | 0.6455 | | | |

5.4.3Minimum Distance Classifier (MD)
The Minimum distance (MD) is a supervised learning algorithmand is used to classify unknown image data to classes ofknown labels by minimizing the distance between the imagedata and the class in multi-feature space [26]. The distancemeasured between the labeled class and unknown imagedata is normally the euclidean distance and is defined as anindex of similarity [27]. Typically, the minimum distance isidentical to maximum similarity. The mean vector of eachclass is used to calculate the euclidean distance from theclass to the unknown pixel. A pixel of the unknown labelis classified to the nearest class unless a distance thresholdis specified as shown in Figure 7. In case a pixel does notmeet the defined criteria, it is labeled as unclassified [28].The euclidean distance is defined mathematically as follow;

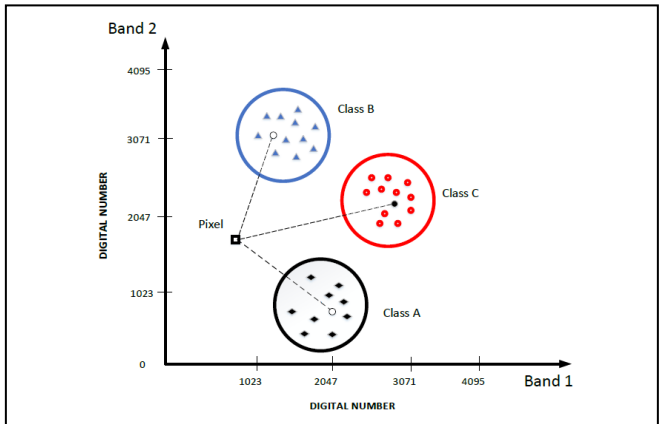


Fig. 7. Schematic Illustration of Minimum Distance Classification

## 6 RESULTS AND DISCUSSION

Classification performance of the three different supervisedclassifiers i.e., ANN, SVM and MD is presented in theform of confusion matrix in Table 4, Table 5 and Table 6,respectively. The results have been calculated and assessedin terms of producer's accuracy, user's accuracy, overallaccuracy and Kappa Coefficient. The classified map for allthe three classifiers i.e., ANN, SVM and MD are shownin Figure 9(a), Figure 9(b) and Figure 9(c), respectively.

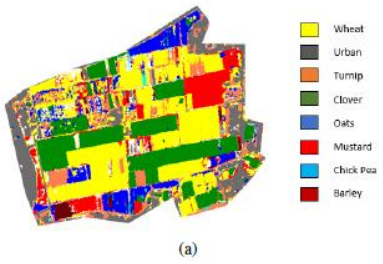


Fig. 9. (a). ANN Classified Map

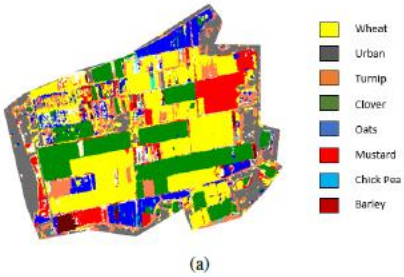


Fig. 9. (b). SVM Classified Map

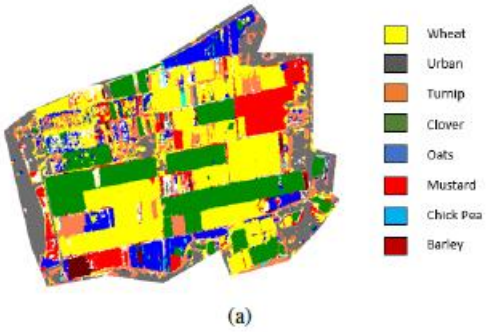


Fig. 9. (c). MD Classified Map

The Figure 8(a) shows the performance comparison betweenthese three classifiers in terms of producer accuracy. It canbe observed that the ANN classifier has better produceraccuracy for the entire classes as compared to SVM andMD classifiers. More specifically, the producer accuracyfor wheat class is 99:53% for ANN classifier, while SVMand MD classify with an accuracy of 90:30% and 69:58%,respectively. Thus, the ANN classifier has achieved betteraccuracy on the classification map with the least number ofomission errors as compared to SVM and MD. Similarly, itcan be observed that the user accuracy of the ANN classifieris higher than the other two techniques for most of the classesas clear from figure 8(b). However, it is observed that theANN classifier has slightly lower user accuracy for wheat,Oats and Chick Pea as compared to SVM classifier as clearfrom Figure 8(b). More specifically, the user accuracy of98:95% for wheat class in ANN classifier is slightly lowerthan 99:56% user accuracy for SVM classifier, while MD hasthe lowest i.e. 89:01% user accuracy value. Therefore, it canbe concluded that the SVM classifier has a marginal gain of0:61% with reference to the user accuracy performance of theANN classifier. However, keeping in view the performancegain of 9:23% in the producer accuracy of the ANN classifierwith reference to the SVM classifier the marginal gain of0:61% in the user accuracy of the SVM classifier has lowerimpact on the overall accuracy, relative to the ANN classifier.Furthermore, its observed that although the user accuracyperformance of both the ANN and SVM classifiers is better,the MD classifier has the lowest user accuracy performancefor all the considered classes. The overall accuracy andKappa Coefficient performance for all the three classifiers ispresented in Figure 8(c). It is evident that the ANN classifieroutperforms SVM and MD classifiers as shown in figure 8(c).The overall accuracy for ANN classifier is 98:7031% witha Kappa Coefficient of 0:9825, which is much higher thanthe SVM's overall accuracy of 85:2% and Kappa Coefficientof 0:81. Moreover, the MD classifier has the lowest overallaccuracy of 73:1604% and Kappa Coefficient value of 0:646.

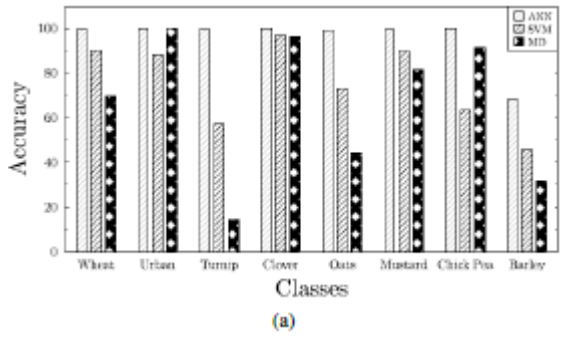


Fig. 8. (a). Producer Accuracies of ANN, SVM and MD classifiers

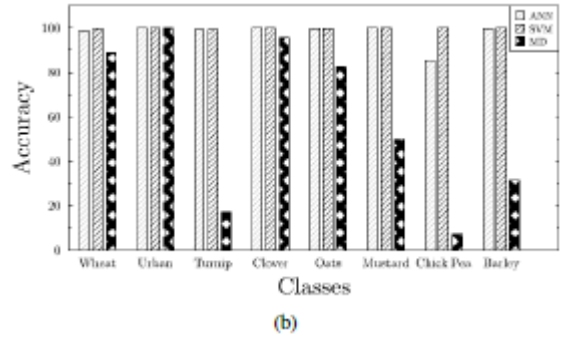


Fig. 8. (b). User Accuracies of ANN, SVM and MD classifiers

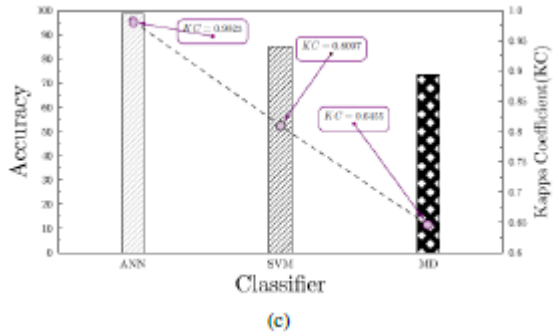


Fig. 8. (c). Overall Accuracies Kappa Coefficient of ANN, SVM and MD classifiers

## 7 Conclusion

Accurate and timely generation of agricultural crop statistics play a vital role in proper agricultural management. In thisresearch paper, we focus on the land cover classificationof wheat crop using remotely sensed multi-spectral planet-scope temporal data. Furthermore, we have utilized machinelearning paradigm for the automated classification of landcover. The planet-scope imagery used in our research workis a temporal stack of multi-date imagery obtained on multipledates with reference to the phenological wheat cycle.Furthermore, three different machine learning classifiers i.e.Artificial Neural Network (ANN), Support Vector Machine(SVM) and Minimum Distance (MD) classifiers are used forthe wheat crop classification. Performance analysis of theseclassifiers is carried out with the aid of confusion matrixand Kappa Coefficient values. The results obtained showthat the ANN classifier results in the best producer accuracyperformance of 99:53% for the wheat class, while in SVMand MD it is 90:30% and 69:58%, respectively. Thus theANN classifier results in better wheat classification accuracyin terms of classification of wheat on the classification mapwith the least number of omission errors as compared toboth the SVM and MD classifiers. Furthermore, the ANNclassifier with an overall accuracy of 98:70% and Kappa Coefficientvalue of 0:98 outperforms SVM and MD classifiershaving an overall accuracy of 85.2005% and 73.1604% andKappa Coefficient values of 0.8097 and 0.6455, respectively.Moreover, it is observed that the MD classifier has the lowestoverall accuracy of 73:16% and Kappa Coefficient value of0:64. In nutshell, the advanced machine learning techniquesperforms much better than the naive technique.

### Acknowledgments

- The financial support of National Center of Big data and Cloud Computer (NCBC), University of Engineering and Technology, Peshawar, under the auspices of Higher Education Commission, Pakistan is gratefully acknowledged.
- The data-grant support of Planet INC in provisioning of Planet-Scope Dove Satellites Imagery is also gratefully acknowledged.

## References

[1] A. A. Chandio, J. Yuansheng, T. Rahman, M. N. Khan, X. Guangshun, and Z. Zhi, “Analysis of agricultural subsectors contribution growth ratein the agriculture gdp growth rate of pakistan,” International Journal ofHumanities and Social Science Invention, vol. 4, no. 8, pp. 101–105, 2015.

[2] “Pakistan grain and feed annual,” ://www.agripunjab.gov.pk/overview

[3] “Agriculture department pakistan statistics,” https://apps.fas.usda.gov/newgainapi/api/report/downloadreportbyfilename?filename=Grain%20and%20Feed%20Annual_Islamabad_Pakistan_3-28-2019.pdf, accessed: 2020-05-2.

[4] D. Poli, F. Remondino, E. Angiuli, and G. Agugiaro, “Radiometric andgeometric evaluation of geoeye-1, worldview-2 and pléiades-1a stereoimages for 3d information extraction,” ISPRS Journal of Photogrammetryand Remote Sensing, vol. 100, pp. 35–47, 2015.

[5] R. Hooda, M. Yadav, and M. Kalubarme, “Wheat production estimationusing remote sensing data: An indian experience,” in Workshop Proceedings: Remote Sensing Support to Crop Yield Forecast and Area Estimates, Stresa, Italy. 30 Nov.–1 Dec. 2006., 2006, pp. 85–89.

[6] M.-C. Cheng and C. Zhang, “‘formosat-2 for international societal benefits,” Remote Sensing, vol. 2016, 2016.

[7] P. Team, “Planet application program interface: In space for life on earth,” San Francisco, CA, vol. 2017, p. 40, 2017.

[8] “Finance division,” http://www.finance.gov.pk, accessed: 2020-02-2.

[9] H. Mu, L. Zhou, X. Dang, and B. Yuan, “Winter wheat yield estimationfrommultitemporal remote sensing images based on convolutional neuralnetworks,” in 2019 10th International Workshop on the Analysis of MultitemporalRemote Sensing Images (MultiTemp). IEEE, 2019, pp. 1–4.

[10] Ö. Vanlı, A. Sabuncu, and Z. D. U. Avcı, “Regional classification of winterwheat using remote sensing data in southeastern turkey,” in 2019 8th InternationalConference on Agro-Geoinformatics (Agro-Geoinformatics). IEEE, 2019, pp. 1–4.

[11] F. Xu, Z. Li, S. Zhang, N. Huang, Z. Quan, W. Zhang, X. Liu, X. Jiang, J. Pan, and A. V. Prishchepov, “Mapping winter wheat with combinationsof temporally aggregated sentinel-2 and landsat-8 data in shandongprovince, china,” Remote Sensing, vol. 12, no. 12, p. 2065, 2020.

[12] C.-j. LI, J.-h. WANG, W. Qian, D.-c. WANG, X.-y. SONG, W. Yan, and W.-j. HUANG, “Estimating wheat grain protein content using multitemporalremote sensing data based on partial least squares regression,” Journal of Integrative Agriculture, vol. 11, no. 9, pp. 1445–1452, 2012.

[13] P. Yang, Q. Zhou, Z. Chen, Y. Zha, W. Wu, and R. Shibasaki, “Estimationof regional crop yield by assimilating multi-temporal tm images into cropgrowth model,” in 2006 IEEE International Symposium on Geoscience andRemote Sensing. IEEE, 2006, pp. 2259–2262.

[14] S. Xiaoyu, C. Bei, Y. Guijun, and F. Haikuan, “Comparison of winterwheat growth with multi-temporal remote sensing imagery,” in Proceedingsof Conference Series on Earth and Environmental Science, 2014, pp. 1–7.

[15] J. Liu, P. Chen, and X. Xu, “Estimating wheat coverage using multispectralimages collected by unmanned aerial vehicles and a new sensor,” in 2018 7th International Conference on Agro-geoinformatics (Agrogeoinformatics). IEEE, 2018, pp. 1–5.

[16] M. Du and N. Noguchi, “Monitoring of wheat growth status and mappingof wheat yield’s within-field spatial variations using color images acquiredfromuav-camera system,” Remote sensing, vol. 9, no. 3, p. 289, 2017.

[17] W. Zhuo, J. Huang, L. Li, X. Zhang, H. Ma, X. Gao, H. Huang, B. Xu, and X. Xiao, “Assimilating soil moisture retrieved from sentinel-1 andsentinel-2 data into wofost model to improve winter wheat yield estimation,” Remote Sensing, vol. 11, no. 13,

p. 1618, 2019.
[18] L. Liangyun, W. Jihua, S. Xiaoyu, L. Cunjun, H. Wenjiang, and Z. Chunjiang, “Study on winter wheat yield estimation model based on ndvi andseedtime,” in IGARSS 2004. 2004 IEEE International Geoscience andRemote Sensing Symposium, vol. 6. IEEE, 2004, pp. 4045–4047.
[19] N.-B. Chang, C. Mostafiz, Z. Sun, W. Gao, and C.-F. Chen, “Developinga prototype satellite-based cyber-physical system for smart wastewatertreatment,” in 2017 IEEE 14th International Conference on Networking, Sensing and Control (ICNSC). IEEE, 2017, pp. 339–344.
[20] Y. Zhongcheng, W. Fengge, and Z. Junsuo, “Research of a constructionmethod of space-based cyber-physical system,” in 2016 Chinese Controland Decision Conference (CCDC). IEEE, 2016, pp. 6862–6866.
[21] A. Mirkouei, “A cyber-physical analyzer system for precision agriculture,” J Environ SciCurr Res, vol. 3, p. 016, 2020.
[22] National Center for Big Data Cloud Computing, UET Peshawar, GeoSurvey. [Online]. Available: https://play.google.com/store/apps/details?id=com.ncbc.survey.gis&hl=en
[23] K. Perumal and R. Bhaskaran, “Supervised classification performance ofmultispectral images,” arXiv preprint arXiv:1002.4046, 2010.
[24] M. A. Hearst, S. T. Dumais, E. Osuna, J. Platt, and B. Scholkopf, “Supportvector machines,” IEEE Intelligent Systems and their applications, vol. 13, no. 4, pp. 18–28, 1998.
[25] M. Ustuner, F. B. Sanli, and B. Dixon, “Application of support vectormachines for landuse classification using high-resolution rapideye images: A sensitivity analysis,” European Journal of Remote Sensing, vol. 48, no. 1, pp. 403–422, 2015.
[26] A. Wacker and D. Landgrebe, “Minimum distance classification in remotesensing,” LARS Technical Reports, p. 25, 1972.
[27] K. Yang, A. Pan, Y. Yang, S. Zhang, S. H. Ong, and H. Tang, “Remotesensing image registration using multiple image features,” Remote Sensing, vol. 9, no. 6, p. 581, 2017.
[28] B. Ankayarkanni and A. E. S. Leni, “A new statistical rule model forimage retrieval system of remote sensing images,” in 2016 InternationalConference on Circuit, Power and Computing Technologies (ICCPCT). IEEE, 2016, pp. 1–5